Design and Development of a Multidimensional Personalized Recommender System

Synopsis

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INTRODUCTION

Recent advancement in technology has significantly changed the way one can collect and access information. It enables dealing with making the information universe friendly, understandable, and useful by filtering out noisy elements, finding useful nuggets of information on demand, and creating new knowledge. However, an increase in the amount of generated information results in information overload which has become a ubiquitous problem in modern society (Yera & Martinez, 2017; Fu, Li, Liu, Pirkkalainen & Salo, 2020; and Long et al., 2022). One of the solutions to reduce this information overload is the use of recommender systems (Long et al., 2022).

1.1 The Recommender System

A recommender system is an information filtering system that presents user-relevant information by creating a profile of the user and comparing it to the other existing reference characteristics stored in the database. It deals with the problem of information overload by filtering vital information fragments from dynamically generated information according to the user's preferences, interests, or observed behavior about an item (Yera & Martinez, 2017).

The goals of recommender systems are to provide relevant, novel, and serendipity recommendations to the users while increasing recommendation diversity. Some of the soft goals of a recommendation system include providing overall user satisfaction and customized user experience. Most recommender systems take either of two basic approaches:

a. Collaborative Filtering

Collaborative filtering is a method of filtering the interests of a user by collecting preferences from many users. This approach aggregates ratings, recognizes similarities between individuals, and generates recommendations based on inter-user comparisons (Ekstrand, Riedl & Konstan, 2011). The assumption is that the individual ratings represent fairly constant opinions and analyzing this can provide a reasonable estimate of the actual individual preferences. The benefit of this approach includes simplicity as it focuses on only the item rated highly by peers which reduce workload and can be applied to almost any type of content.

b. Content based filtering

Content-based filtering methods are based on the description of the items and a profile of the user's preferences. These algorithms recommend items that are similar to those that a user liked in the past or is examining in the present.

The framework of a Recommender System

The components of a Recommender System, shown in Figure 1, comprise the database, the API, and the recommender engine. The database stores information about users, their ratings, and items. The API collects or communicates information from/to users and items. The recommender engine generates recommendations for users based on the produced and stored information.

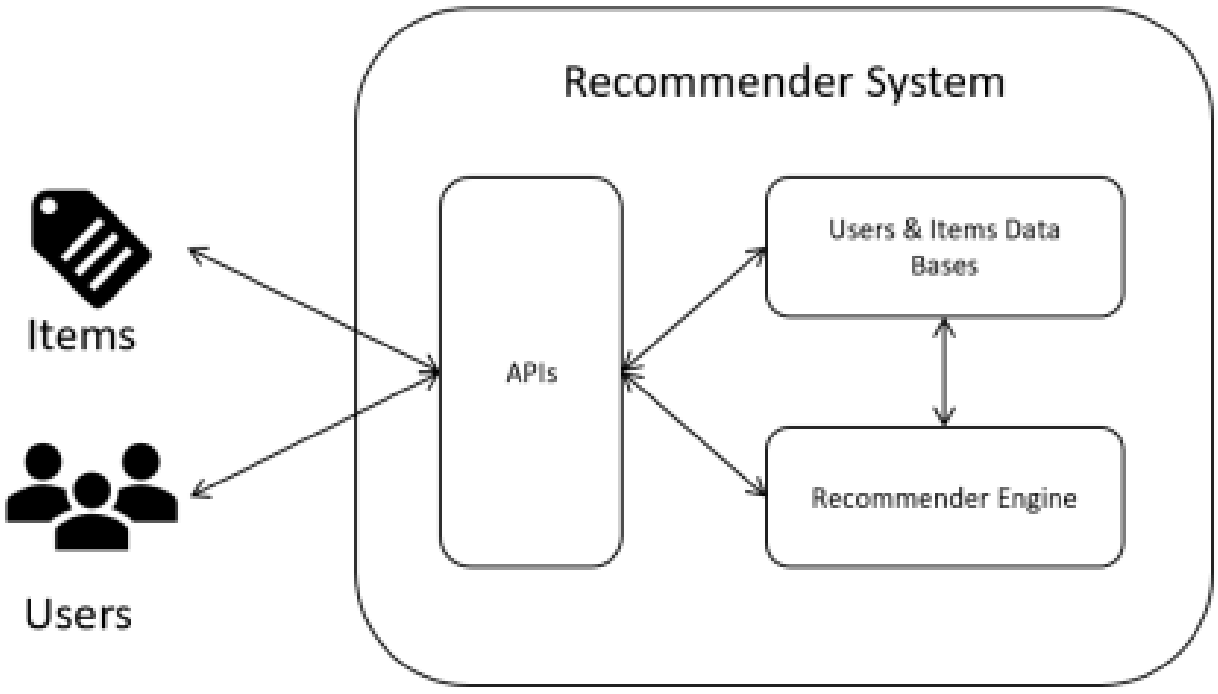

Figure 1 Components of a Recommender System
(Source: Tejeda-Lorente, Bernabé-Moreno, Herce-Zelaya, Porcel & Herrera-Viedma, 2018)

The framework of a recommender system is shown in Figure 2. The similarity between users can be estimated using different approaches ranging from the classical similarity measures used in information retrieval to machine learning techniques.

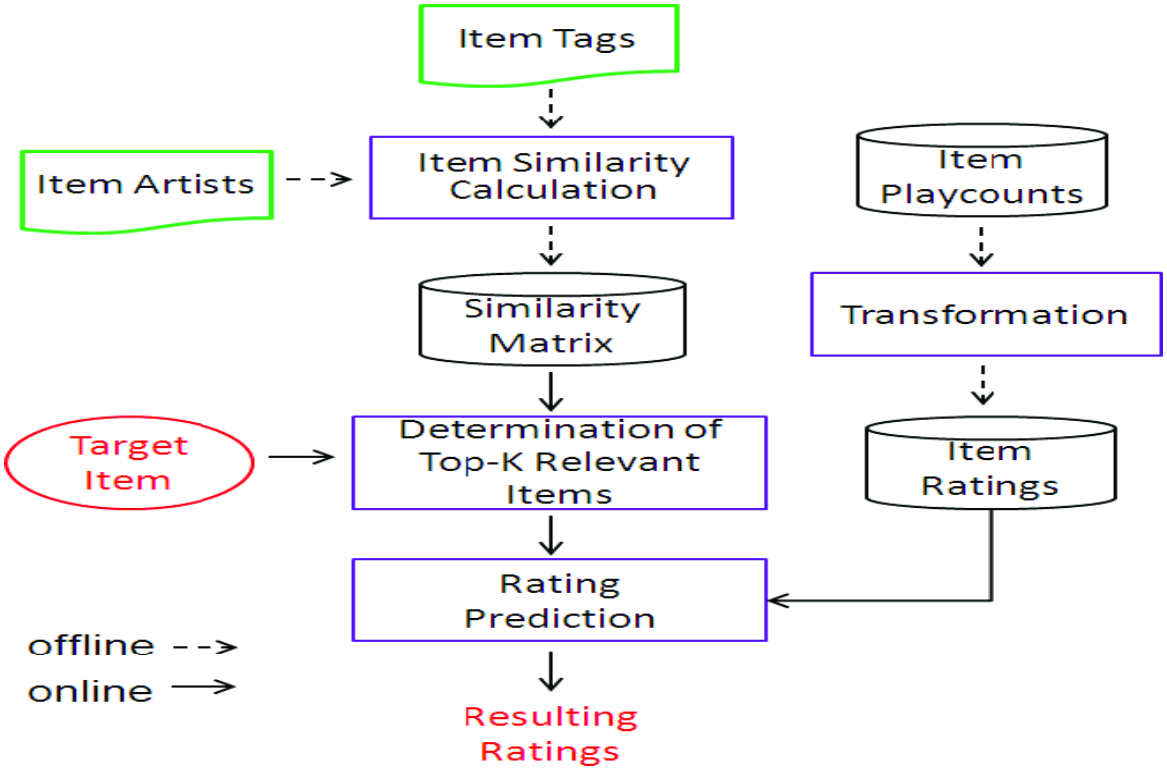

Figure 2 The framework of a Recommender system
(Source: Jallouli, Lajmi & Amous, 2017)

Types of Recommender Systems

A recommender system can be of the following types:

1. Neighborhood-based Recommender System

These types of systems (Bellogín & De Vries, 2013 and Kużelewska, 2020) consider the preferences of the neighborhood users before making recommendations to the active user. The system finds all the users similar to the active user who had similar preferences in the past and then makes predictions regarding all unknown products that the active user has not rated but are being rated in their neighborhood.

These systems are also called similarity-based recommender systems due to similarity calculation, and are also called collaborative filtering recommender systems since preferences are considered collaboratively from a pool of users. The Neighborhood-based systems can be classified as:

a. User-based collaborative filtering: The basic idea here is that people with similar tastes in the

past will like similar items in the future as well.

b. *Item-based collaborative filtering:* Here similarity between items is used instead of similarity between users. This reduces the computational cost as the item catalog does not change rapidly, and therefore re-computation is not required very often.

2. Personalized Recommender System

A personalized recommendation system (Xiao, Wang, Jiang & Li, 2018 and Cui et al., 2020) takes into consideration the personalized behavior of the users. The systems can be categorized as:

a. *Content-based Recommender System:* These systems recommend items similar to those that a user liked in the past. On the basis of items' features previously rated by a user, a profile of user interests is built. The recommendation process matches the attributes of the user profile against the attributes of a content object to give suggestions.

b. *Context-Aware Recommender System:* These systems consider the present state of the user (like location, time, or mood), which define the context of the user to provide them the relevant information. Since users have different needs in different contexts, these recommendation systems can capture the context information of the user and refine their suggestions accordingly.

3. Model-based recommender systems

Model-based recommender systems (Aditya, Budi & Munajat, 2016 and Hrnjica, Music & Softic, 2020) are developed to improve the performance of recommendation engines. Using the available historical data, a model is built with weights learned automatically that are used to make new predictions regarding the products. These results are finally ranked in a specific order before making recommendations.

4. Knowledge-Based Recommender Systems

In these types of systems (Chakrabarti, Ahmad, Jarke & Quix, 2023 and Thorat, Patle & Kashyap, 2023), the recommendation process is based on the similarities between item descriptions and customer requirements, or the use of constraints specifying user requirements. Knowledge-based recommender systems can be classified on the basis of the knowledge as:

a. *Constraint-based recommender systems:* Here users specify constraints on the item attributes. Domain-specific rules are used to match the user requirements to item attributes.

b. *Case-based recommender systems:* In case-based recommender systems, cases are specified by the user as targets. Similarity metrics are defined on the item attributes to retrieve similar items to these cases.

5. Demographic Recommender Systems

In this type of system (Wang, Chan & Ngai, 2012 and Al-Shamri, 2016), the demographic information about the user is combined to learn classifiers that can map specific demographics to ratings or buying propensities. Although demographic recommender systems do not usually provide the best results on a stand-alone basis, they add significantly to the power of other recommender systems as a component of ensemble models. Demographic techniques form *people-to-people* correlations like collaborative ones but use different data.

6. Utility-based Recommender System

These systems (Deng, 2015 and Zheng, 2019) make suggestions on the basis of the computed utility of each object for the user. This approach can factor non-product attributes into the utility computation. This makes it possible to check the real-time inventory of the object and display it to the user.

7. Hybrid recommender systems

A hybrid recommender system (Paradarami, Bastain & Wightman, 2017 and Walek & Fajmon, 2023) combines the advantages of two or more types of recommender systems.

8. Multi-dimensional recommender systems

Various real-life applications, such as recommending vacation packages or Web content to customers, require consideration of multi-dimensions and thus it is not sufficient to recommend items to users. A multidimensional recommender system includes multiple dimensions, aggregated hierarchies, profiling, and a query language. This approach is based on the data warehousing paradigm (Chaudhuri & Dayal, 1997) because it provides support for multiple dimensions and because hierarchies

provide recommendation capabilities at multiple aggregation levels (Adomavicius & Tuzhilin, 2001). Such types of systems are developed by Felden & Chamoni (2007), Nardini et al. (2018), Taghavi, Bentahar, Bakhtiyari & Hanachi (2018) and Zhang, Lee, Lu, Yu & Lu (2023) to allow the users to express a comprehensive class of recommendations "on the fly" as their needs arise.

1.2 Data Warehouse

The data warehouse is one of the most important business intelligence tools for immense data storage, management, and processing. Organizations build data warehouses to analyze what has occurred within the business across time in order to obtain a competitive edge in the marketplace. A data warehouse collects and stores integrated sets of historical data from multiple operational systems. A data warehouse approach includes extraction, transformation, and loading (ETL) operation, statistical functions, data mining capabilities, and client analysis tools to manage the process of gathering data, transforming it into useful and actionable information, and delivering it to business users.

A data warehouse stores credible facts and statistics that a decision-maker is able to retrieve as and when needed. It gathers data from different sources and converts it into a single and widely used format which results in accuracy. Decision makers can quickly access the data in a data warehouse to make quick and accurate decisions.

Data Warehouse Architecture

The basic architecture for a data warehouse is shown in Figure 3. End users directly access data derived from several source systems through the data warehouse.

The data is collected through different heterogeneous sources which then through the ETL process are stored in a data warehouse. The metadata presents the data about the data. The summary data includes lightly or highly summarized data that is updated as the new data loads in the data warehouse. The role of this component is to speed up the query performance. The data warehouse comprises various querying, reporting, and analysis tools that are used by different users of the organization for decision-making.

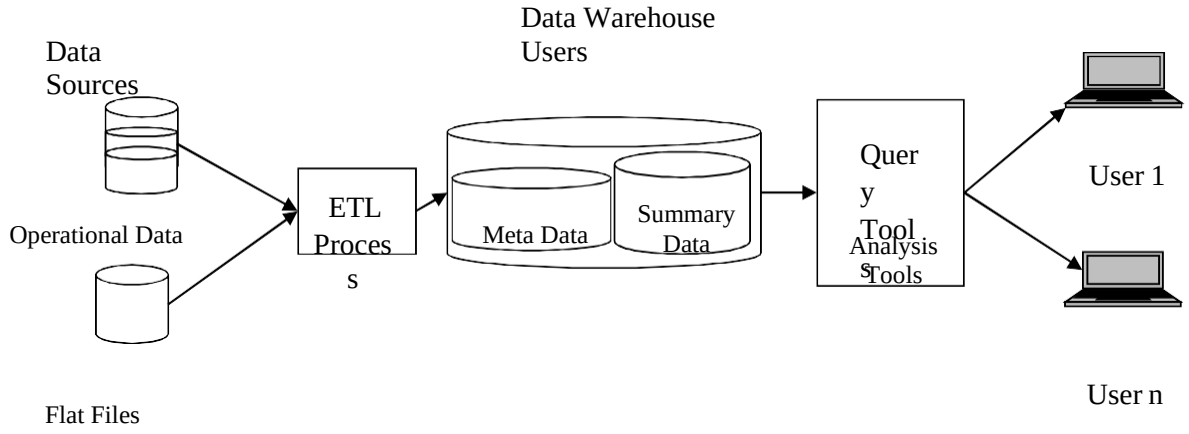

Figure 3 Basic Data Warehouse

1.3 Methods for developing Recommender System

As already discussed, there are various methods for extracting or filtering information from a recommender system. Some of the methods are discussed below:

A. Data Mining

Data mining is the process of discovering and modeling a high volume of data to find unknown patterns. The area has great significance as it enables analyzing data from different perspectives and summarizing it into useful information. Data mining techniques include:

- **Classification:** Classification is the process of generating a function or model that describes and distinguishes data classes. This model then predicts the class label of objects for which the class label is unknown.
- **Feature selection:** Feature selection is the process of detecting relevant features and removing irrelevant, redundant, or noisy data.
- **Clustering:** Clustering is used to structure data vectors by grouping them together into clusters based on their similar properties.
- **Association rules:** Association Rule implies a certain association relationship among a set of objects in a database.

B. Probabilistic approaches

In a probabilistic approach, a probability model is built using the prior probabilities from the available data, and a ranked list of recommendations is generated by calculating the probability of liking or disliking a product for each user. The Naïve Bayes method is an example of this approach.

C. Machine learning approaches

Using historical user and product data, features and output classes are extracted to develop a model in this approach. A final list of ranked product recommendations can then be generated using this model. Machine learning can be classified into four types:

i. Supervised learning

ii. Unsupervised learning

iii. Semi-supervised learning

iv. Reinforcement learning

i. Supervised learning: Supervised learning algorithms are provided with training data and correct answers. This gained knowledge is then applied to real data. Supervised learning algorithms include:

- **Regression:** It is mainly used for prediction, forecasting, time series modeling, and determining the causal-effect relationship between variables.
- **Classification:** It uses the dataset or observations provided to learn how to categorize new observations into various classes or groups.
- **Neural networks:** These use interconnected nodes or neurons in a layered structure that resembles the human brain.
- **Support vector machine:** This, based on statistical learning theory, is used for classification purposes.
- **K-nearest neighbor:** It is a non-parametric algorithm that classifies data points based on their proximity and association with other available data.
- **Random forest:** It is used for both classification and regression purposes.

ii. Unsupervised Learning: Unsupervised learning algorithms focus on finding hidden patterns in data. Unsupervised learning algorithms include:

- **Clustering:** Clustering is the task of dividing the data sets into a certain number of clusters in such a manner that the data points belonging to a cluster have similar characteristics.
- **Association:** this checks for the dependency of one data item on another data item and maps accordingly. The algorithm is used to determine some interesting relations or associations among the variables of the dataset.
- **Dimensionality reduction:** It is a way of converting the higher dimensions dataset into lesser dimensions dataset ensuring that it provides similar information.

iii. Semi-supervised learning: Semi-supervised learning algorithms are able to learn and draw conclusions even with incomplete data.

iv. Reinforcement Learning: The reinforcement learning algorithm learns by feedback mechanisms and past experiences.

D. Mathematical approaches: In these approaches, the ratings or interaction information of users on products are assumed to be simple matrices. Mathematical approaches are applied to these matrices to predict the missing ratings for the users. The most commonly used approaches are the matrix factorization model and single-valued decomposition models.

1.4 Data warehouse tools

The information can be extracted from the masses of data stored in a data warehouse by analyzing the data. Popular data warehouse tools for this are:

- Online Analytical Processing (OLAP)
- Data Mining
- A wide array of statistical functions, including descriptive statistics, hypothesis testing, correlation analysis, test for distribution fit, cross tabs with Chi-square statistics, and ANOVA.

Online Analytical Processing (OLAP)

OLAP tools are used to organize large business databases and support business intelligence.

OLAP databases are divided into one or more cubes, and each cube is organized such that data can be easily retrieved and analyzed.

A cube is the data structure that aggregates the measures by the levels and hierarchies of each of the dimensions that can be analyzed. For example, a cube combines time, geography, and product lines with summarized data, such as sales or inventory figures.

The source data for OLAP is Online Transactional Processing (OLTP) databases that are commonly stored in data warehouses. OLAP data is derived from this historical data and is aggregated into structures that are useful in sophisticated analysis.

OLAP databases contain two basic types of data:

- **Measures**: are a set of values in a cube that is based on a column in the cube's fact table and are usually numeric values. Measures are the central values in the cube that are preprocessed, aggregated, and analyzed; and
- **Dimensions**: are a set of one or more organized hierarchies of levels in a cube that a user understands and uses as the base for data analysis.

Literature survey

Researchers are using various tools and techniques to enhance the performance of the recommender system. An overview of the research done for improving the performance of different types of recommender systems is presented below.

2.1 Knowledge Recommender System

A knowledge recommender system is a system that uses knowledge discovery and learning tools to generate recommendations. Li & She (2017) developed a Bayesian generative model, the collaborative variational autoencoder that considers both rating and content for recommendation in multimedia scenarios. The model learned deep latent representations from content data in an unsupervised manner and also learned implicit relationships between items and users from both content and rating. Tarus, Niu & Khadidja (2017) combined collaborative filtering and ontology to recommend personalized learning materials to online learners with different characteristics such as

learning style, study level, and skills level. The technique alleviated the cold-start problem at the initial stages of recommendation by using ontological knowledge in the absence of sufficient ratings. Tarus, Niu & Yousif (2017) developed a hybrid knowledge-based recommender system using sequential pattern mining with ontology for recommending learning resources to learners in an e-learning environment. Ontology was used to represent knowledge about the learner and learning resources while the sequential pattern mining algorithm was used to discover the learner's historical sequential learning patterns. Wei, He, Chen, Zhou & Tang (2017) developed two recommendation models to address the problems of complete cold start and incomplete cold start items. The models combined a time-aware collaborative filtering model, timeSVD++, with a deep learning architecture, SDAE. SDAE was responsible for extracting the item content features, and the timeSVD++ model was responsible for the prediction of unknown ratings. Yanes, Sassi & Ghezala (2017) presented an ontology-based recommender system to help developers identify relevant Commercial Off-The-Shelf components that best meet their needs. This recommender system considered knowledge about the items through an ontology. Yi, Li, Feng & Shi (2017) implemented a movie recommender system based on the traditional user-based collaborative filtering algorithm and the user project scoring matrix. A graph database was chosen to deal with the relation. The degree of recommendation of films was then distinguished by color and size, allowing users to have a better experience.

Ibrahim, Yang, Ndzi, Yang & Al-Maliki (2018) developed a framework for the ontology-based personalized course recommendation to integrate the information from multiple sources based on the hierarchical ontology similarity to provide students with appropriate recommendations. Khallouki, Abatal & Bahaj (2018) designed and implemented a mobile tourism recommendation system using context awareness. The system combined Internet of Things technologies with semantic web services to predict the tourist real-time context and provide suitable services. Li et al. (2018) developed an ontology and rule-based inference engine by providing consolidated recommendations on both the design and manufacturing process to provide designers with an automatic and interactive guide during the early design stage. Previous design knowledge and the current situation of manufacturing

constraints were effectively shared and reused. Nilashi, Ibrahim & Bagherifard (2018) dealt with sparsity and scalability in recommender systems using dimensionality reduction and ontology techniques. Ontology was used to improve the accuracy of recommendations in collaborative filtering. A dimensionality reduction technique, singular value decomposition, was used to find the most similar items and users in each cluster to improve the scalability of the recommendation method. Sun & Zhang (2018) presented a unified framework to integrate recommender systems and dialogue system technologies for developing an intelligent conversational recommender system that optimizes per session-based utility function. Taneja & Arora (2018) developed a cross domain-multi dimension tensor factorization method to implement the cross-domain recommendation for alleviating the sparsity, scalability, cold- start, and serendipity problems. A comparative analysis of cross-domain and single-domain recommendation systems was performed on Movie-Lens and Book-Crossing datasets. Zhao et al. (2018) developed a recommender system by modelling the sequential interactions between users. A Markov decision process was combined with reinforcement learning to automatically learn the optimal strategies via recommending trial-and-error items and receiving reinforcements of these items from users' feedback.

Kouki, Schaffer, Pujara, Donovan & Getoor (2019) dealt with generating and visualizing personalized explanations for hybrid recommender systems. A hybrid probabilistic graphical model was developed to generate real-time recommendations along with personalized explanations. Mohanty et al. (2019) provided a fuzzy-based web page recommendation framework with a user profile and ontology design. The weblog documents were gathered using the Internet of Things to clean the data and undergo the learning process. The profile ontology module was used to sparse the learner profile as the ontology. For identification of the similar data, a similarity measure method was utilized. The generated rules were optimized with the help of the chicken swarm optimization technique. Rupasingha & Paik (2019) dealt with an ontology-based clustering approach that used domain specificity and service similarity for ontology generation. The user ratings were then predicted by calculating the trust value between different users. Selvan, Vairavasundaram & Ravi

(2019) implemented a fuzzy ontology-based food- drug recommendation system for diabetic patients. The system was capable of extracting patient disease history, discovering important risk factors using wearable sensors, and forecasting patient health conditions using fuzzy ontology to make food and medicine recommendations. This system enabled the physicians to extract the correct data for diagnosis. Selvaraj, Burugari, Sumathi, Nayak & Tripathy (2019) presented a recommendation system using a semantic similarity measure that refined the input query for generating multiple queries. The system provided an optimized query search based on the developed algorithm and implemented the cache memory management service system to provide the answer supporting system for the given query. Xue et al. (2019) presented an item-based collaborative filtering solution based on deep neural networks, DeepICF, to provide top-N item recommendations as the potential structure of real-world data is non-linear. The model effectively learned the higher-order relations among items from data in a non-linear way of neural networks. Logesh, Subramaniyaswamy, Vijayakumar & Li (2020) presented a bio-inspired clustering ensemble by aggregating swarm intelligence and fuzzy clustering models for user-based collaborative filtering. The developed recommendation approaches were evaluated on the Yelp and TripAdvisor databases for recommendation accuracy and stability through standard evaluation metrics.

Li, Abel & Negre (2021) focused on methods to recommend collaborators for users within the collaboration context. Ontology based semantic similarity was employed in a collaboration context to generate context-aware collaborator recommendations for users. Ray, Garain & Sarkar (2021) proposed a hotel recommendation system using sentiment analysis of the hotel reviews, and aspect-based review categorization which works on the queries given by a user. Wang et al. (2021) developed a method to evaluate Traditional Chinese Medicine prescriptions included in the officially recommended list, as well as other well-known prescriptions for treating flu-like diseases using ontology-based side-effect prediction framework and artificial neural network based deep learning methods.

Agarwal, Mishra & Kolekar (2022) built a knowledge-based recommendation system that used

multiple domain ontologies and operated on semantically related usage data. This recommender system employed cluster-based collaborative filtering in conjunction with rules written in the semantic web rule language. Kang, Lee, Kweon & Yu (2022) developed a dubbed personalized hint regression method for distilling the preference knowledge in a balanced way without relying on any assumption on the representation space or any method-specific hyperparameters. To circumvent the clustering, the method employed a personalization network to enable a personalized distillation of the student space for each user/item representation. Wang, Joty, Gao, Zeng & Wong (2022) developed a method to discover and extract internal knowledge from a context. Both entity-level and contextual-level representations were captured to jointly model user preferences for the recommendation. Time-aware attention was designed to emphasize the recently appeared items in entity-level representations. A multi-domain dataset, OpenDialKG, was also taken to show the effectiveness of the model. Wang, Zhou, Wen & Zhao (2022) implemented a unified conversational recommender system, UniCRS, based on knowledge-enhanced prompt learning. The approach unified the recommendation and conversation subtasks into the prompt learning paradigm and utilized knowledge-enhanced prompts based on a fixed pre-trained language model to fulfill both subtasks in a unified approach. Fused knowledge representations, task-specific soft tokens, and the dialogue context were included in the prompt design for providing sufficient contextual information to adapt the fixed pre-trained language model for the conversational recommendation task. Weichselbraun, Waldvogel, Fraefel, van Schie & Kuntschik (2022) introduced a method for building a comprehensive knowledge graph from the education providers' Web pages. Educational programs from 488 providers and leverage entity recognition and entity linking methods were collected in conjunction with contextualization to extract knowledge on entities such as prerequisites, skills, learning objectives, and course content. Slot filling integrated these entities into an extensive knowledge graph. A recommender system leverages the created graph, and background knowledge on occupations to provide a career path and upskilling suggestions. Wu, He, Ming & Goh (2022) developed a service- oriented knowledge recommender framework focusing on the mechanism of

knowledge service transfer and the knowledge recommendation model. This comprised of the knowledge service demanders, knowledge service providers, and platform operators. A fuzzy synthetic evaluation method was developed using multi-factor fuzzy decision-making techniques to improve the quality of the knowledge service.

Chakrabarti, Ahmad, Jarke & Quix (2023) developed a rule-based visualization recommendation system, VizRec, to provide an intelligent assistant for guiding users directly to relevant insights in the data. The system automated the aspects of visualization design and recommended visualizations incorporating both the data characteristics and the diverse tasks representing users' goals. A knowledge-based rule engine was used to derive the knowledge-based rules to ensure the correctness of these. A formalization theory was also presented considering the dynamic nature of the rule engine. Lai et al. (2023) introduced a workload-aware deep learning query recommendation approach to address the limited use of the sequential information from the preceding query and the predefined syntactic

features used to compare queries. Thorat, Patle & Kashyap (2023) applied the dual operator, transition probability function, and convolution neural network for processing the pest's image discretely and continuously to apply the recommended insecticide. The proposed system combined pest identification and insecticide recommendation using a machine vision convolution neural network. The soil nutrient analysis was performed using a soil sensor with the recommendation of fertilizers according to the obtained nutrient values. Zhao, Wang, Liang & Chen (2023) established a clustering hierarchical progressive improvement model by integrating cluster analysis and context-dependent data envelopment analysis methods. These clusters based on students' ontological features were used to stratify students of different classes and calculate measures, such as obstacles, to determine the reference path for individuals with inefficient learning processes.

2.2 Multi-criteria Recommender System

Multi-Criteria Decision Making (MCDA) methods have been increasingly applied to improve recommendations when multiple criteria are considered in Recommender Systems. Dewi, Sari, Widodo, Astungkoro & Aziz (2020) implemented a mobile application for sports venue recommendations with

specific attribute weighting to accommodate user preference for a specific attribute using the TOPSIS algorithm. The reason for choosing TOPSIS was the low level of algorithm complexity and its suitability for mobile devices. The system took the user's location coordinates and then recommended a Futsal court based on location, price, and the number of courts. Jun, Kim, Rhee & Chang (2020) implemented an embedding-based collaborative filtering housing recommendation system for analyzing the nonlinear housing preference of individuals. The model mapped users and items in each dense vector space which are called embedding layers. It reflected trade-offs between the alternatives and recommended unexpected housing items and thus improving rational housing decision-making. Al Fararni et al. (2021) developed a recommender system based on big data technologies, artificial intelligence, and operational research to promote tourism in Morocco, specifically in the Daraa-Tafilalet region. The system not only recommended the list of tourist attractions according to tourist preferences but was also considered as a trip planner as it helped in designing a detailed travel program including heterogeneous tourism resources for specific visit duration. Forouzandeh, Berahmand, Nasiri & Rostami (2021) implemented a recommendation system in the tourism industry by combining the artificial bee colony algorithm and the fuzzy TOPSIS model to make hotel recommendations for the users. Hong & Jung (2021) developed two single tensor models consisting of countries (user), items, multi-criteria ratings, and cultural groups, to consider simultaneously an inherent structure and interrelations of these factors into recommendation processes.

An & Moon (2022) applied sentiment analysis technology using a deep neural network to sightseeing reviews, add ratings to reviews that had not included them, and supplemented data to enable various classifications by weather or season. A system was designed to enable custom recommendations based on this data. Asemi, Asemi, Ko & Alibeigi (2022) developed a multi-criteria recommender system by using fuzzy multi-criteria decision-making for weighting the properties of the recommender system based on human judgment. Dridi, Tamine & Slimani (2022) integrated multiple contexts and multiple criteria to improve items rating prediction. Criteria referred to the items' attributes, while Context denoted the circumstances in which the user uses an item. The recommender's data was

examined from the graph theory based perspective by representing three types of entities (users, contextual situations, and criteria) as well as their relationships as a tripartite graph. A high-order co-clustering was performed on the tripartite graph for simultaneously partitioning the graph entities representing users in similar contextual situations and their evaluated item criteria. Hikmawati, Maulidevi & Surendro (2022) developed a multi-criteria recommender system to determine the worth and risk of various regions, based on several constraints and databases. The model utilized the analytical network process to discover interconnectedness and feedback and included the weighting technique also. The study was carried out in 27 districts in West Java, Indonesia. A robustness analysis of three different item-based multi-criteria top-*n* recommendation methods was performed by Kaya & Kaleli (2022). New and existing evaluation criteria were used for measuring the effectiveness of attacks. Pelissari, Alencar, Amor & Duarte (2022) presented the preliminary results of a literature review by following Kitchenham's guidelines to demonstrate the application of multi-criteria decision-making methods in a recommender system and concluded that these methods can be applied in two phases: the preference elicitation and the recommendation phases. Peng, Wang & Wang (2022) developed multi-criteria decision-making methods based on *Z*-numbers and their projection measure and fusion techniques. An optimization model was introduced to determine the potential probability distributions involved in *Z*-numbers. An improved multi-objective optimization method was developed by integrating ratio analysis with the full multiplicative form method. Concepts of content-based recommendation and collaborative filtering recommendation methods were applied to hotel selection problems. Lifestyle, poor diet, and stress strongly contribute to aggravating people's health problems. Teixeira, Martinho, Novais, Corchado & Marreiros (2022) designed a diabetic-friendly recommender system for diabetic people to find suitable restaurants nearby. The diabetic-friendly feature was built using a multi-agent system that considered the user preferences and recommended the user with potentially benefited lifestyle and health. A case-based reasoning algorithm was applied to improve the solution and sentiment analysis was used for identifying the restaurant reviews score. Torkayesh et al. (2022) presented a framework of a recommender system by integrating life cycle assessment and multi-

criteria decision-making to assess the sustainability of waste management systems. These approaches were used individually also with relevant sustainability criteria and related standards to present a set of recommendations for ensuring scientifically robust, meaningful, and reliable decisions. Zheng & Wang (2022) implemented a multi-criteria recommendation framework to directly infer a ranking score for an item candidate from the predicted ratings on multiple criteria.

Shambour, Al-Zyoud, Hussein & Kharma (2023) implemented a hybrid content-based multi- criteria collaborative filtering approach for helping patients find the best-suited doctors who meet their preferences accurately. The method exploited multi-criteria decision-making, doctor reputation score, and content information of doctors to increase the quality of recommendations and reduce the influence of data sparsity. Shrivastava, Sisodia & Nagwani (2023) developed a deep neural network-based multi-stakeholder recommendation system to aggregate consumer and producer preferences. A multi-criteria rating-based interaction matrix was generated to learn the producers' preferences for an item. A deep neural network-based model training was also performed to generate the cumulative preference matrix by learning and aggregating the preferences of consumer and producer stakeholders.

2.3 Personalized Recommender System

These systems analyze the user data with other users in more detail to deliver customized recommendations. Xiao, Wang, Jiang & Li (2018) implemented a personalized recommendation system for learners in online courses. The system recommended learning resources such, as relevant courses to learners enrolled in formal online courses, by using a combination of association rules, content filtering, and collaborative filtering. Pilot testing of this system indicated that this recommendation system improved the utilization rate of educational resources and also promoted learning autonomy. Logesh, Subramaniyaswamy, Vijayakumar & Li (2019) developed an activity and behavior-induced personalized recommender system to predict the persuasive point of interest recommendations. A new group recommendation model was implemented to meet the requirements of the group of users by exploiting relationships between them. Cui et al. (2020) developed a recommendation model based on a time correlation coefficient and a K-means with a cuckoo search. Similar users were clustered together

for a quick and accurate recommendation. The designed personalized recommendation model based on preference patterns improved the quality of the model as it was capable of analyzing the user's behaviors. Al-Ghobari, Muneer & Fati (2021) implemented a location-aware personalized traveler assistance by integrating user preferences and the global positioning system to generate personalized and location-aware recommendations. The system utilized the K-Nearest algorithm to match the name and category tags with the user's input. Personalized suggestions also provided suggestions on the basis of nearby popular attractions using the Google point of interest feature to enhance system usability. Abbasi-Moud, Vahdat-Nejad & Sadri (2021) implemented a tourism recommendation system to extract users' preferences for providing personalized recommendations. The system semantically compared the preferences of a user with the features of attractions to suggest the most matching points of interest to the user. Asani, Vahdat-Nejad & Sadri (2021) implemented a context-aware recommender system to extract the food preferences of individuals from their comments and suggested restaurants in accordance with these preferences. The semantic approach was used to cluster the name of foods extracted from users' comments and analyze their sentiments about them. Choi, Ryu & Kim (2021) implemented a travel recommender system to help tourists build their personalized travel plans by integrating collaborative filtering with constraint satisfaction filtering.

According to Chaudhuri, Sarma & Samanta (2022) the existing recommendation models emphasized only on user's preference rather than the user's intention which may change with time. Thus, a hidden attribute-based recommendation engine was implemented that utilized a feature engineering technique to unfold valuable insights into papers through multiple hidden features. These features were used as a context for users as well as multiple criteria for ranking papers. The system also predicted the user's intention beyond the user's preference to capture the dynamic notion of a user. Fu, Tian & Tang (2022) implemented a personalized recommendation system for teaching resources to provide resource information and identify inaccurate resource allocation. Geng et al. (2022) developed an explainable recommendation system, a visually-enhanced approach, using visualization generation and text–image matching discrimination to improve not only the text quality but also the diversity and

explainability of the generated explanations. Ghobakhloo & Ghobakhloo (2022) used a machine learning approach to focus on identifying customer needs by extracting opinion and sentiment analysis, and quantifying customers' sentiment orientation. The approach was used to design a recommender system for providing appropriate services according to customer satisfaction, sentiment, and experiences. The customers' opinions and experiences were obtained by evaluating tweets containing hashtags with the titles and headings of banking services as a statistical population. Tang & Yu (2022) designed a personalized recommendation system for English teaching resources based on the multi-*K* nearest neighbor regression algorithm to ensure the quality of resource recommendation. A resource browsing function module, teaching resource detailed page recommendation module, and teaching resource database was designed for the system. The multi-*K* nearest neighbor regression algorithm based missing data reconstruction algorithm of English teaching resources was developed. Zhao, Su, Rao & Chen (2022) built a recommender system for social commerce that combines rich information about social network users and products on an e-commerce platform. The user's textual information, and the tags and the relationships between users were considered in building the user profiling model. A topic model was adopted, and a feedback mechanism was also designed. The collaborative filtering method and clustering algorithm were integrated to obtain a high recommendation accuracy. Kong et al. (2022) analyzed the possibility of applying collaborative filtering to the insurance industry using real customer data from South Korea. Using three different collaborative filtering models, the relevance of applying these models was examined to insurance products under various situations by comparing them with logistic-regression-based recommendation models.

Huang, Lu & Yang (2023) applied AI-enabled personalized video recommendations to stimulate students' learning motivation and engagement during a systems programming course in a flipped classroom setting. Students were assigned to control and experimental groups comprising 59 and 43 college students, respectively. The students in both groups received flipped classroom instruction, but only those in the experimental group received AI-enabled personalized video recommendations. Students' engagement was quantitatively measured based on their learning profiles in a learning

management system. The results revealed that the AI-enabled personalized video recommendations significantly improved the learning performance and engagement of students with a moderate motivation level. Lee, Zhou, Yang, Du & Pan (2023) implemented a recommendation system that jointly utilized social relationships and historical behaviors, based on the extended linear optimization technique. The performance of the algorithm was tested for four groups of users on real networks. Zhang et al. (2023) implemented a recommendation system based on the big data of operators. The system mined users' behavior characteristics and used a machine learning method to predict the possibility of users accepting the recommended products.

Hybrid Recommender System

This is a special class of recommender system built by combining two types of recommender systems. Paradarami, Bastain & Wightman (2017) developed a method for predicting the ratings using an artificial neural network framework, where both collaborative and content-based features were used to train the model. This methodology integrated content, collaborative, and metadata associated with ratings under the framework of a unified supervised learning model to produce better prediction results than memory-based collaborative filtering recommendation systems. Rodríguez-García, Valencia-García, Colomo-Palacios & Gómez-Berbís (2019) presented a hybrid recommender system and integrated case-based reasoning and knowledge-based techniques to perform recommendations in the dating domain. The authors demonstrated that the application of semantic technologies integrated with external repositories of information generated a more detailed user profile that has a direct effect on the system performance and the quality of the recommendations. Walek & Fajmon (2023) implemented a hybrid recommender system by combing a recommender module composed of three subsystems that use collaborative-filtering and content-based approaches, and a fuzzy expert system. The system considered user preferences and their activity on the e-shop, and the resulting list of recommended products is created using the fuzzy expert system.

2.4 Multi-dimensional Recommender System

In many applications, the flexibility of recommendation, i.e., the capability of handling multiple

dimensions and various recommendation types is very important. Xia et al. (2021) developed a deep network recommendation model with three modalities–picture, review, and scoring. A unified deep neural network was developed including an embedding layer, pooling layer, and fully connected layer. A knowledge model for tourist hotels based on the analysis of user-generated data was developed to provide practical guidance for hotel managers and users. Esheiba, Helal, Elgammal & El-Sharkawi (2022) developed a data warehouse-based recommender system that collected and analyzed large volumes of product usage data from similar products to the product that the customer needs to customize by adding IoT smart devices. Noorian, Harounabadi & Ravanmehr (2022) implemented a hybrid approach that combines multidimensional data to enhance personalized trip recommendations while addressing the shortcomings of existing recommender systems, such as their inability to account for dynamic user preferences and diverse contexts. The designed system considered the data sparsity issue and employed a clustering algorithm to reduce the time complexity of discovering points of interest. Zhong, Yang, Fan, Tian & Zhang (2022) implemented a service recommendation system in a cloud-based environment to enable users to select the best services from different cloud providers that match user requirements. The system combined items' attribute information (decision tags) and user's attribute information (decision times) and alleviated the cold-start problems of recommendation systems. A rough multidimensional matrix model based on a cooperative filtering algorithm was also developed.

The motivation for the proposed work

From the above discussion following are the observed research gaps:

- Traditional recommender systems deal with applications that have two types of entities, users and items, for example, providing recommendations based on how users liked items. However, recommendations in real-life situations generally depend on some extra dimensions also, like the time dimension, to model their inherent additional complexities (Fernández-García, Rodriguez-Echeverria, Preciado, Perianez& Gutiérrez, 2022).
- In addition, the traditional recommendation systems ignore the inherent connection between the user's preference and time. However, in reality, the interest of the user varies over time. Thus, a

recommendation system should provide users accurate and fast recommendations with the change of time (Cui et al., 2020).

- Moreover, an effective and personalized recommendation model based on preference patterns can provide a higher quality recommendation by analyzing the user's behaviors (Cui et al., 2020).

Thus, there is a need to develop a recommender system that considers multidimensionality, aggregation hierarchies, and users' preferences and behaviors. This research study is an effort in this direction.

PROPOSED WORK

The main goal of this research study is to develop a personalized recommender system by using a multi-dimensional approach.

Objectives of the proposed study are:

- Design and development of a multidimensional recommender system.
- Development of a query engine to express different types of recommendations.
- Development of a recommendation engine to generate recommendations based on users' preferences and users' behaviors.
- Implementation of the System for a real-life situation.

Methodology for achieving the objectives

1. Development of the Recommender System using multi-dimensional approach

A recommender system will be developed by integrating it with data warehousing approach for identifying patterns from multidimensional data. To remain ahead of other organization, businesses are more interested in performing multidimensional analysis. Thus the data warehousing approach is integrated with the recommender system.

The performance of this system will be compared with other developed recommender system in terms of accuracy, personalization, scalability, and diversity. The comparison will be employed by using performance metrics like precision, recall, and root mean square error, to demonstrate the improvements in recommendation accuracy and personalization. This comparison will use standard

datasets, reflecting key variables such as student preferences, academic performance, time constraints, and location.

2. Development of a query engine to express different types of recommendations

The query engine will be developed to answer the users' queries and provide recommendations using PostgreSQL.

Research component in developing the query engine will be

- Implementation of object-oriented data
- Processing of unstructured data using NLP techniques
- Functioning of the queries in a multidimensional domain

This filtering information will be used to generate appropriate recommendations

The queries will depend upon the education domains and the dimensions concerned for recommendation.

3. Development of a recommendation engine to generate recommendations based on users' preferences and users' behaviors.

Method for recommendations will be developed by integrating multi-criteria decision analysis (MCDA), machine learning (ML), and knowledge engineering (KE) techniques.

The interface will be developed in a manner to get the performances of the users. The data acquisition component will process this information according to the needs of the Recommender System to produce the recommendations.

4. Implementation of the System for a real-life situation

Having defined the goals, the data that will be collected from heterogeneous sources will be stored in a data warehouse and will be provided for information filtering. This study will deal with the variables like time and location, and others based on the application area chosen for the study.

The application domain for this study will be higher education (taking Dayalbagh Educational Institute (Deemed to be University), Agra as a case study, with the goal of suggesting personalized learning paths to students. This will require collecting both structured data from databases and

unstructured data through surveys. Neural computing or deep learning based approach will be used to learn features from images or text data, which can then be used in the proposed recommender system. The consideration of unstructured data will increase the complexity. This will be solved using Multi-Dimensional Analysis and techniques like Natural Language Processing.

Stages of building proposed system

1. **Business lines analysis:** This is an important step in the system development cycle. The main purpose of this phase is to understand and identify the business requirements.
2. **Planning the project iterations:** On the basis of the identified business requirements, priorities will be established, depending on their relative importance. This priority list will be used to establish the subsequent iterations of the system development.

The identified business and technical requirements will be refined for developing the proposed system. All the constraints imposed by the source systems will be identified.

3. **Selection of the technological solution:** In this stage, the possible tools for implementing data and application architecture will be identified to provide technical and support architectural functions.
4. **The System architecture design**: The relevant data will be collected from primary and secondary sources. The system architecture will consist of:

a. The *data architecture* to organize the data sources and define the quality and management standards for the data.

b. The *application architecture* to provide the implementation of the business functionality within the proposed system.

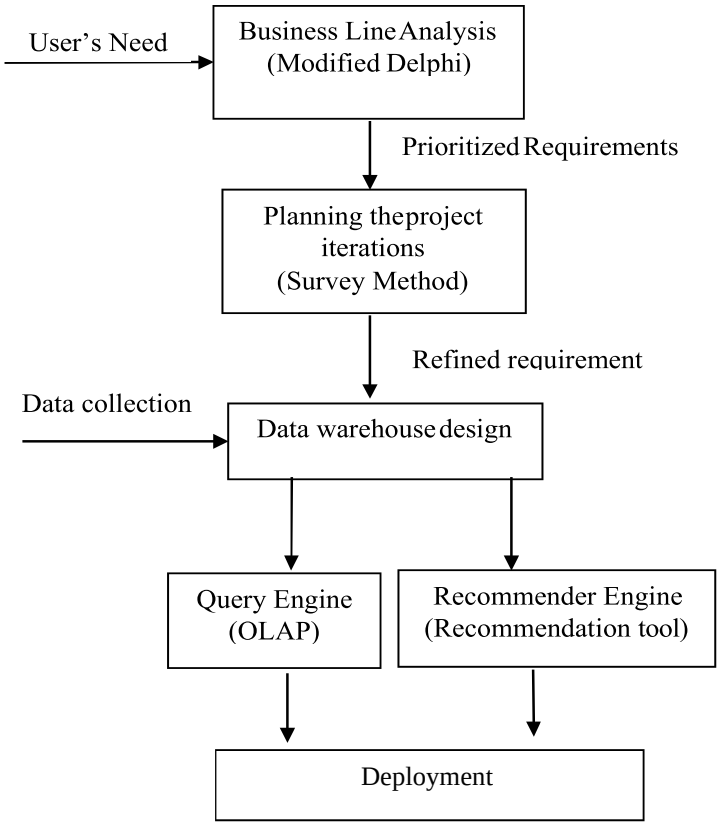

Figure 4: Stages of development

c. The *technical architecture* to provide the infrastructure for data and application architectures.

This will include the server, hardware and software components for connection and communication, and the users' workstations.

5. Data warehouse modeling: In this stage, the database schema will be achieved, metadata will be defined and the data source list will be updated to include all the information necessary for the implementation.

6. Recommendation tool modeling: Different models and algorithms will be deployed to generate recommendations.

7. Testing and implementation: Once the planning and design stages are completed, the current iteration for the proposed system implementation will start. In this stage, the development and testing

environments will be established, the hardware and software components will be installed, and the configuration management process will be implemented.

The architecture of the proposed system will be as shown in Figure 4.

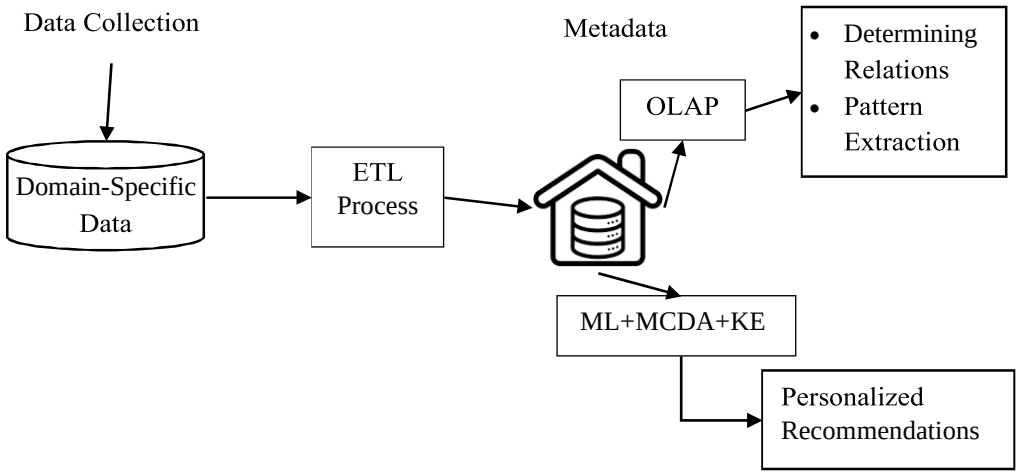

Figure 5: The Architecture of the proposed System The components of the proposed System will be:

i. **The Database:** This component will store the dataset relevant to the application domain. It will establish a one-to-one corresponding relationship with the recommendation engine and will be managed by the recommendation management module.

ii. **Data warehouse:** This component will administrate the dataset in the data warehouse.

iii. **Recommendation Engine:** The recommendation engine will help in generating recommendations by using the developed recommendation models. The recommendation models will be stored in this component to supply different recommendation services and build multiple recommendation models to generate different kinds of recommendations.

iv. **Query Engine:** This component will be used for CRUD (create, read, update and delete) operations as well as executing queries to provide answers to the users.

The capabilities of the proposed system will be

- Generate customized and useful recommendations according to user's interest;
- Ensure that the user does not get repeated recommendations;
- Recommend categories of items to certain types of users;

- Support extensive profiling capabilities;
- The ability to automatically drill from summary and calculated data; and
- Provide extensive and flexible recommendations that can be requested by the user on-the-fly.

REFERENCES

1. Abbasi-Moud, Z., Vahdat-Nejad, H., & Sadri, J. (2021). Tourism recommendation system based on semantic clustering and sentiment analysis. *Expert Systems with Applications*, *167*, 114324.
2. Aditya, P. H., Budi, I., & Munajat, Q. (2016, October). A comparative analysis of memory-based and model-based collaborative filtering on the implementation of recommender system for E- commerce in Indonesia: A case study PT X. In *2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS)* (pp. 303-308). IEEE.
3. Adomavicius, G., & Tuzhilin, A. (2001, August). Extending recommender systems: A multidimensional approach. In *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI-01), Workshop on Intelligent Techniques for Web Personalization (ITWP2001), Seattle, Washington, August* (pp. 4-6).
4. Agarwal, A., Mishra, D. S., & Kolekar, S. V. (2022). Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs. *Cogent Engineering*, *9*(1), 2022568.
5. Al Fararni, K., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., & Sabri, A. (2021). Hybrid recommender system for tourism based on big data and AI: A conceptual framework. *Big Data Mining and Analytics*, *4*(1), 47-55.
6. Al-Ghobari, M., Muneer, A., & Fati, S. M. (2021). Location-aware personalized traveler recommender system (lapta) using collaborative filtering KNN. *Computers, Materials and Continua*, *69*(2), 1553-1570.
7. Al-Shamri, M. Y. H. (2016). User profiling approaches for demographic recommender systems. *Knowledge-Based Systems*, *100*, 175-187.
8. An, H. W., & Moon, N. (2022). Design of recommendation system for tourist spot using

sentiment analysis based on CNN-LSTM. *Journal of Ambient Intelligence and Humanized Computing*, *13*(3), 1653-1663.

9. Asani, E., Vahdat-Nejad, H., & Sadri, J. (2021). Restaurant recommender system based on sentiment analysis. *Machine Learning with Applications*, *6*, 100114.
10. Asemi, A., Asemi, A., Ko, A., & Alibeigi, A. (2022). An integrated model for evaluation of big data challenges and analytical methods in recommender systems. *Journal of big data*, *9*(1), 1-26.
11. Bellogín, A., & De Vries, A. P. (2013, September). Understanding similarity metrics in neighbour- based recommender systems. In *Proceedings of the 2013 Conference on the Theory of Information Retrieval* (pp. 48-55).
12. Chakrabarti, A., Ahmad, F., Jarke, M., & Quix, C. (2023). Monitoring Large Scale Production Processes Using a Rule-Based Visualization Recommendation System. *SN Computer Science*, *4*(1), 1-24.
13. Chaudhuri, A., Sarma, M., & Samanta, D. (2022). SHARE: Designing multiple criteria-based personalized research paper recommendation system. *Information Sciences*, *617*, 41-64.
14. Chaudhuri, S., & Dayal, U. (1997). An overview of data warehousing and OLAP technology. *ACM Sigmod record*, *26*(1), 65-74.
15. Choi, I. Y., Ryu, Y. U., & Kim, J. K. (2021). A recommender system based on personal constraints for smart tourism city. *Asia Pacific Journal of Tourism Research*, *26*(4), 440-453.
16. Cui, Z., Xu, X., Fei, X. U. E., Cai, X., Cao, Y., Zhang, W., & Chen, J. (2020). Personalized recommendation system based on collaborative filtering for IoT scenarios. IEEE Transactions on Services Computing, 13(4), 685-695.
17. Deng, F. (2015, April). Utility-based recommender systems using implicit utility and genetic algorithm. In *2015 International Conference on Mechatronics, Electronic, Industrial and Control Engineering (MEIC-15)* (pp. 860-864). Atlantis Press.
18. Dewi, R. K., Sari, Y. A., Widodo, A. W., Astungkoro, F. P., & Aziz, N. I. M. (2020). Testing for Recommendation Method in M-Health Sports Venue Recommendation System.

International Journal of Innovative Technology and Exploring Engineering (IJITEE), *9*(6), 2143-2146.

19. Dridi, R., Tamine, L., & Slimani, Y. (2022). Exploiting context-awareness and multi-criteria decision making to improve items recommendation using a tripartite graph-based model. *Information Processing & Management*, *59*(2), 102861.
20. Ekstrand, M. D., Riedl, J. T., &Konstan, J. A. (2011). Collaborative filtering recommender systems. *Foundations and Trends® in Human–Computer Interaction*, *4*(2), 81-173.
21. Esheiba, L., Helal, I. M., Elgammal, A., & El-Sharkawi, M. E. (2022). A Data Warehouse-Based System for Service Customization Recommendations in Product-Service Systems. *Sensors*, *22*(6), 2118.
22. Felden, C., & Chamoni, P. (2007, January). Recommender systems based on an active data warehouse with text documents. In *2007 40th Annual Hawaii International Conference on System Sciences (HICSS'07)* (pp. 168a-168a). IEEE.
23. Fernández-García, A. J., Rodriguez-Echeverria, R., Preciado, J. C., Perianez, J., & Gutiérrez, J. D. (2022). A hybrid multidimensional Recommender System for radio programs. *Expert Systems with Applications*, *198*, 116706.
24. Forouzandeh, S., Berahmand, K., Nasiri, E., & Rostami, M. (2021). A hotel recommender system for tourists using the Artificial Bee Colony Algorithm and Fuzzy TOPSIS Model: a case study of tripadvisor. *International Journal of Information Technology & Decision Making*, *20*(01), 399-429.
25. Fu, R., Tian, M., & Tang, Q. (2022). The Design of Personalized Education Resource Recommendation System under Big Data. *Computational Intelligence and Neuroscience*, *2022*.
26. Fu, S., Li, H., Liu, Y., Pirkkalainen, H., & Salo, M. (2020). Social media overload, exhaustion, and use discontinuance: Examining the effects of information overload, system feature overload, and social overload. *Information Processing & Management*, *57*(6), 102307.
27. Geng, S., Fu, Z., Ge, Y., Li, L., de Melo, G., & Zhang, Y. (2022, May). Improving Personalized

Explanation Generation through Visualization. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (pp. 244-255).

28. Ghobakhloo, M., & Ghobakhloo, M. (2022). Design of a personalized recommender system using sentiment analysis in social media (case study: banking system). *Social Network Analysis and Mining*, *12*(1), 1-16.
29. Hikmawati, E., Maulidevi, N. U., &Surendro, K. (2022, September). Multi-Criteria Recommender System for Determining Risk Level of Covid-19. In *2022 9th International Conference on Advanced Informatics: Concepts, Theory and Applications (ICAICTA)* (pp. 1-6). IEEE.
30. Hong, M., & Jung, J. J. (2021). Multi-criteria tensor model for tourism recommender systems. *Expert Systems with Applications*, *170*, 114537.
31. Hrnjica, B., Music, D., & Softic, S. (2020). Model-based recommender systems. *Trends in Cloud- based IoT*, 125-146.
32. Huang, A. Y., Lu, O. H., & Yang, S. J. (2023). Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. *Computers & Education*, *194*, 104684.
33. Ibrahim, M. E., Yang, Y., Ndzi, D. L., Yang, G., & Al-Maliki, M. (2018). Ontology-based personalized course recommendation framework. IEEE Access, 7, 5180-5199.
34. Jallouli, M., Lajmi, S., & Amous, I. (2017). Designing recommender system: conceptual framework and practical implementation. *Procedia computer science*, *112*, 1701-1710.
35. Jun, H. J., Kim, J. H., Rhee, D. Y., & Chang, S. W. (2020). "SeoulHouse2Vec": An embedding-based collaborative filtering housing recommender system for analyzing housing preference. *Sustainability*, *12*(17), 6964.
36. Kang, S., Lee, D., Kweon, W., & Yu, H. (2022). Personalized Knowledge Distillation for Recommender System. *Knowledge-Based Systems*, *239*, 107958.
37. Kaya, T. T., & Kaleli, C. (2022). Robustness Analysis of Multi-Criteria Top-n Collaborative

Recommender System. *Arabian Journal for Science and Engineering*, 1-24.

38. Khallouki, H., Abatal, A., & Bahaj, M. (2018, May). An ontology-based context awareness for smart tourism recommendation system. In Proceedings of the International Conference on Learning and Optimization Algorithms: Theory and Applications (pp. 1-5).
39. Kong, H., Yun, W., Joo, W., Kim, J. H., Kim, K. K., Moon, I. C., & Kim, W. C. (2022). Constructing a personalized recommender system for life insurance products with machine□ learning techniques. *Intelligent Systems in Accounting, Finance and Management*.
40. Kouki, P., Schaffer, J., Pujara, J., O'Donovan, J., & Getoor, L. (2019, March). Personalized explanations for hybrid recommender systems. In *Proceedings of the 24th International Conference on Intelligent User Interfaces* (pp. 379-390).
41. Kużelewska, U. (2020, June). Dynamic neighbourhood identification based on multi-clustering in collaborative filtering recommender systems. In *International Conference on Dependability and Complex Systems* (pp. 410-419). Springer, Cham.
42. Lai, E. Y., Zolaktaf, Z., Milani, M., AlOmeir, O., Cao, J., & Pottinger, R. (2023). Workload-Aware Query Recommendation Using Deep Learning.
43. Lee, Y. L., Zhou, T., Yang, K., Du, Y., & Pan, L. (2023). Personalized recommender systems based on social relationships and historical behaviors. *Applied Mathematics and Computation*, *437*, 127549.
44. Li, S., Abel, M. H., & Negre, E. (2021, May). Ontology-based semantic similarity in generating context-aware collaborator recommendations. In 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD) (pp. 751-756). IEEE.
45. Li, X., & She, J. (2017, August). Collaborative variational autoencoder for recommender systems. In Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 305-314).
46. Li, Z., Zhou, X., Wang, W. M., Huang, G., Tian, Z., & Huang, S. (2018). An ontology-based product design framework for manufacturability verification and knowledge reuse. The

International Journal of Advanced Manufacturing Technology, 99(9), 2121-2135.

47. Logesh, R., Subramaniyaswamy, V., Malathi, D., Sivaramakrishnan, N., & Vijayakumar, V. (2020). Enhancing recommendation stability of collaborative filtering recommender system through bio-inspired clustering ensemble method. *Neural Computing and Applications*, *32*(7), 2141-2164.
48. Logesh, R., Subramaniyaswamy, V., Vijayakumar, V., & Li, X. (2019). Efficient user profiling based intelligent travel recommender system for individual and group of users. *Mobile Networks and Applications*, *24*(3), 1018-1033.
49. Long, X., Sun, J., Dai, H., Zhang, D., Zhang, J., Chen, Y., ... & Zhao, B. (2022). The Choice Overload Effect in Online Recommender Systems: Theoretical Framework and Field Experiment. *Available at SSRN 3890056*.
50. Mohanty, S. N., Rejina Parvin, J., Vinoth Kumar, K., Ramya, K. C., Sheeba Rani, S., & Lakshmanaprabu, S. K. (2019). Optimal rough fuzzy clustering for user profile ontology based web page recommendation analysis. Journal of Intelligent & Fuzzy Systems, 37(1), 205-216.
51. Nardini, F. M., Orlando, S., Perego, R., Raffaetà, A., Renso, C., & Silvestri, C. (2018). Analysing trajectories of mobile users: from data warehouses to recommender systems. In *A Comprehensive Guide Through the Italian Database Research Over the Last 25 Years* (pp. 407-421). Springer, Cham.
52. Nilashi, M., Ibrahim, O., & Bagherifard, K. (2018). A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques. Expert Systems with Applications, 92, 507-520.
53. Noorian, A., Harounabadi, A., &Ravanmehr, R. (2022). A novel Sequence-Aware personalized recommendation system based on multidimensional information. *Expert Systems with Applications*, *202*, 117079.
54. Paradarami, T. K., Bastian, N. D., & Wightman, J. L. (2017). A hybrid recommender system using artificial neural networks. *Expert Systems with Applications*, *83*, 300-313.

55. Pelissari, R., Alencar, P., Amor, S. B., & Duarte, L. T. (2022). A systematic review of the use of multiple criteria decision aiding methods in recommender systems: preliminary results. In *Workshop of Multi-Objective Recommender Systems (MORS'22), in conjunction with the 16th ACM Conference on Recommender Systems, RecSys* (Vol. 22, p. 2022).
56. Peng, H. G., Wang, X. K., & Wang, J. Q. (2022). New MULTIMOORA and pairwise evaluation- based MCDM methods for hotel selection based on the projection measure of Z- numbers. *International Journal of Fuzzy Systems*, *24*(1), 371-390.
57. Ray, B., Garain, A., & Sarkar, R. (2021). An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. *Applied Soft Computing*, *98*, 106935.
58. Rodríguez-García, M. Á., Valencia-García, R., Colomo-Palacios, R., & Gómez-Berbís, J. M. (2019). BlindDate recommender: A context-aware ontology-based dating recommendation platform. *Journal of Information Science*, *45*(5), 573-591.
59. Rupasingha, R. A., & Paik, I. (2019). Alleviating sparsity by specificity□aware ontology based clustering for improving web service recommendation. IEEJ Transactions on Electrical and Electronic Engineering, 14(10), 1507-1517.
60. Selvan, N. S., Vairavasundaram, S., & Ravi, L. (2019). Fuzzy ontology-based personalized recommendation for internet of medical things with linked open data. Journal of Intelligent & Fuzzy Systems, 36(5), 4065-4075.
61. Selvaraj, P., Burugari, V. K., Sumathi, D., Nayak, R. K., & Tripathy, R. (2019, December). Ontology based recommendation system for domain specific seekers. In 2019 Third International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 341-345). IEEE.
62. Shambour, Q. Y., Al-Zyoud, M. M., Hussein, A. H., & Kharma, Q. M. (2023). A doctor recommender system based on collaborative and content filtering. *International Journal of Electrical & Computer Engineering (2088-8708)*, *13*(1).

63. Shrivastava, R., Sisodia, D. S., &Nagwani, N. K. (2023). Deep neural network-based multi-stakeholder recommendation system exploiting multi-criteria ratings for preference learning. *Expert Systems with Applications*, *213*, 119071.
64. Sun, Y., & Zhang, Y. (2018, June). Conversational recommender system. In The 41st international acm sigir conference on research & development in information retrieval (pp. 235-244).
65. Taghavi, M., Bentahar, J., Bakhtiyari, K., & Hanachi, C. (2018). New insights towards developing recommender systems. *The computer journal*, *61*(3), 319-348.
66. Taneja, A., & Arora, A. (2018). Cross domain recommendation using multidimensional tensor factorization. *Expert Systems with Applications*, *92*, 304-316.
67. Tang, Y., & Yu, Y. (2022). A personalized recommendation system for English teaching resources based on multi-K nearest neighbor regression algorithm. *Security and Communication Networks*, *2022*.
68. Tarus, J. K., Niu, Z., & Yousif, A. (2017). A hybrid knowledge-based recommender system for e- learning based on ontology and sequential pattern mining. *Future Generation Computer Systems*, *72*, 37-48.
69. Tarus, J., Niu, Z., & Khadidja, B. (2017). E-learning recommender system based on collaborative filtering and ontology. *International Journal of Computer and Information Engineering*, *11*(2), 256-261.Teixeira, B., Martinho, D., Novais, P., Corchado, J., &Marreiros, G. (2022). Diabetic-Friendly Multi-agent Recommendation System for Restaurants Based on Social Media Sentiment Analysis and Multi-criteria Decision Making. In *EPIA Conference on Artificial Intelligence* (pp. 361-373). Springer, Cham.
70. Tejeda-Lorente, Á., Bernabé-Moreno, J., Herce-Zelaya, J., Porcel, C., & Herrera-Viedma, E. (2018). Adapting recommender systems to the new data privacy regulations. In *New Trends in Intelligent Software Methodologies, Tools and Techniques* (pp. 373-385). IOS Press.
71. Thorat, T., Patle, B. K., & Kashyap, S. K. (2023). Intelligent insecticide and fertilizer

recommendation system based on TPF-CNN for smart farming. *Smart Agricultural Technology*, *3*, 100114.

72. Torkayesh, A. E., Rajaeifar, M. A., Rostom, M., Malmir, B., Yazdani, M., Suh, S., & Heidrich, O. (2022). Integrating life cycle assessment and multi criteria decision making for sustainable waste management: key issues and recommendations for future studies. *Renewable and Sustainable Energy Reviews*, *168*, 112819.
73. Walek, B., &Fajmon, P. (2023). A hybrid recommender system for an online store using a fuzzy expert system. *Expert Systems with Applications*, *212*, 118565.
74. Wang, L., Joty, S., Gao, W., Zeng, X., & Wong, K. F. (2022). Improving Conversational Recommender System via Contextual and Time-Aware Modeling with Less Domain-Specific Knowledge. *arXiv preprint/ arXiv:2209.11386*.
75. Wang, X., Zhou, K., Wen, J. R., & Zhao, W. X. (2022, August). Towards Unified Conversational Recommender Systems via Knowledge-Enhanced Prompt Learning. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (pp. 1929-1937).
76. Wang, Y., Chan, S. C. F., & Ngai, G. (2012, December). Applicability of demographic recommender system to tourist attractions: a case study on trip advisor. In *2012 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology* (Vol. 3, pp. 97- 101). IEEE.
77. Wang, Z., Li, L., Song, M., Yan, J., Shi, J., & Yao, Y. (2021). Evaluating the traditional chinese medicine (TCM) officially recommended in China for COVID-19 using ontology-based side-effect prediction framework (OSPF) and deep learning. Journal of Ethnopharmacology, 272, 113957.
78. Wei, J., He, J., Chen, K., Zhou, Y., & Tang, Z. (2017). Collaborative filtering and deep learning based recommendation system for cold start items. Expert Systems with Applications, 69, 29-39.
79. Weichselbraun, A., Waldvogel, R., Fraefel, A., van Schie, A., &Kuntschik, P. (2022). Building

Knowledge Graphs and Recommender Systems for Suggesting Reskilling and Upskilling Options from the Web. *Information*, *13*(11), 510.

80. Wu, Z., He, L., Ming, X., & Goh, M. (2022). Service-oriented knowledge recommender system and performance evaluation in industrial product development. *International Journal of Production Research*, *60*(20), 6226-6247.
81. Xia, H., An, W., Liu, G., Hu, R., Zhang, J. Z., & Wang, Y. (2021). Smart recommendation for tourist hotels based on multidimensional information: a deep neural network model. *Enterprise Information Systems*, 1-25.
82. Xiao, J., Wang, M., Jiang, B., & Li, J. (2018). A personalized recommendation system with combinational algorithm for online learning. *Journal of Ambient Intelligence and Humanized Computing*, *9*(3), 667-677.
83. Xue, F., He, X., Wang, X., Xu, J., Liu, K., & Hong, R. (2019). Deep item-based collaborative filtering for top-n recommendation. ACM Transactions on Information Systems (TOIS), 37(3), 1- 25.
84. Yanes, N., Sassi, S. B., & Ghezala, H. H. B. (2017). Ontology-based recommender system for COTS components. Journal of Systems and Software, 132, 283-297.
85. Yera, R., & Martínez, L. (2017). A recommendation approach for programming online judges supported by data preprocessing techniques. *Applied Intelligence*, *47*(2), 277-290.
86. Yi, N., Li, C., Feng, X., & Shi, M. (2017, November). Design and implementation of movie recommender system based on graph database. In *2017 14th Web Information Systems and Applications Conference (WISA)* (pp. 132-135). IEEE.
87. Zhang, H., Lee, S., Lu, Y., Yu, X., & Lu, H. (2023). A Survey on Big Data Technologies and Their Applications to the Metaverse: Past, Current and Future. *Mathematics*, *11*(1), 96.
88. Zhang, M., Su, F., Li, Y., Zhou, G., Xin, L., & Ren, T. (2023). Internet of Vehicles Product Recommendation Algorithm and Implementation Based on Ensemble Learning. In *Signal and Information Processing, Networking and Computers* (pp. 1475-1483). Springer, Singapore.

89. Zhao, J., Su, B., Rao, X., & Chen, Z. (2022). A Cross-Platform Personalized Recommender System for Connecting E-Commerce and Social Network. *Future Internet*, *15*(1), 13.
90. Zhao, L. T., Wang, D. S., Liang, F. Y., & Chen, J. (2023). A recommendation system for effective learning strategies: An integrated approach using context-dependent DEA. *Expert Systems with Applications*, *211*, 118535.
91. Zhao, X., Xia, L., Zhang, L., Ding, Z., Yin, D., & Tang, J. (2018, September). Deep reinforcement learning for page-wise recommendations. In *Proceedings of the 12th ACM Conference on Recommender Systems* (pp. 95-103).
92. Zheng, Y. (2019, April). Utility-based multi-criteria recommender systems. In *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing* (pp. 2529-2531).
93. Zheng, Y., & Wang, D. (2022). Multi-Criteria Ranking: Next Generation of Multi-Criteria Recommendation Framework. *IEEE Access*, *10*, 90715-90725.
94. Zhong, D., Yang, G., Fan, J., Tian, B., & Zhang, Y. (2022). A service recommendation system based on rough multidimensional matrix in cloud-based environment. *Computer Standards & Interfaces*, *82*, 103632.